Intercomparison of statistical models for projecting winter oilseed rape yield in Europe under climate change

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Outline

- Introduction
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- Results
  - Prediction power
  - Inference power
  - Uncertainty
- Conclusions

INTRODUCTION

Some challenges in crop modelling

- Formualted and fitted to the same data
- Based on the past
- The true model is unknown
- Model uncertainties
- Ensemble models
- Pest & disease

Global Change Biology

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Multimodel ensembles of wheat growth: many models are better than one

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Process Based Models vs. Statistical models in projecting future yields

Process based models	Statistical models
Include several modules	All-in-one
Dynamic	Static
Based on several valuable studies	Empirical and difficult to interpret without prior knowledge
Require calibration	Easier to use
Complicated	Easily understandable
Uncertainty analysis is difficult	Uncertainty analysis can be done easily
Pest & disease correlation with climate variation is often absent	They can indirectly show some ”hidden” correlations

Application of statistical methods in yield predictions: Previous studies

- Ordinary Least Squares regression
  - Some studies using quadratic terms/ other regression techniques
- Limited to annual or seasonal averages (of temperature and precipitaion)
- No systematic intercomparison of statistical techniques
- Less focus on uncertainty analysis

MATERIALS & METHODS

Data

- Climate data
  - Daily temperature, precipitation, radiation
    - Monthly (3*12 parameters) and fortnightly (3*26 parameters) averages over the daily climatic data
- Winter oilseed rape (yield and sowing date)
  - Denmark, Germany, Czech, (France, Belgium)
  - More than 1000 unique (site/year) observations
  - Covering more than 20 years of data up to 2013

Response function

$$\text{Yield} = T_1 * \text{TEMP}_1 + \ldots + T_n * \text{TEMP}_n$$
$$+ P_1 * \text{PREC}_1 + \ldots + P_n * \text{PREC}_n$$
$$+ R_1 * \text{RAD}_1 + \ldots + R_n * \text{RAD}_n$$
$$+ \text{YE} * \text{Year}$$

Monthly resolution: 37 parameters

Forthnightly resoulution: 79 parameters

Regression Techniques

- Ordinary Least Squars
- Stepwise regression
- PCR
- PLSR
- Shrinkage methods
  - Ridge
  - Elastic Nets (with alpha values of 0.25, 0.50 and 0.75)
  - Lasso

(R Packages: stats, glmnet, plsr)

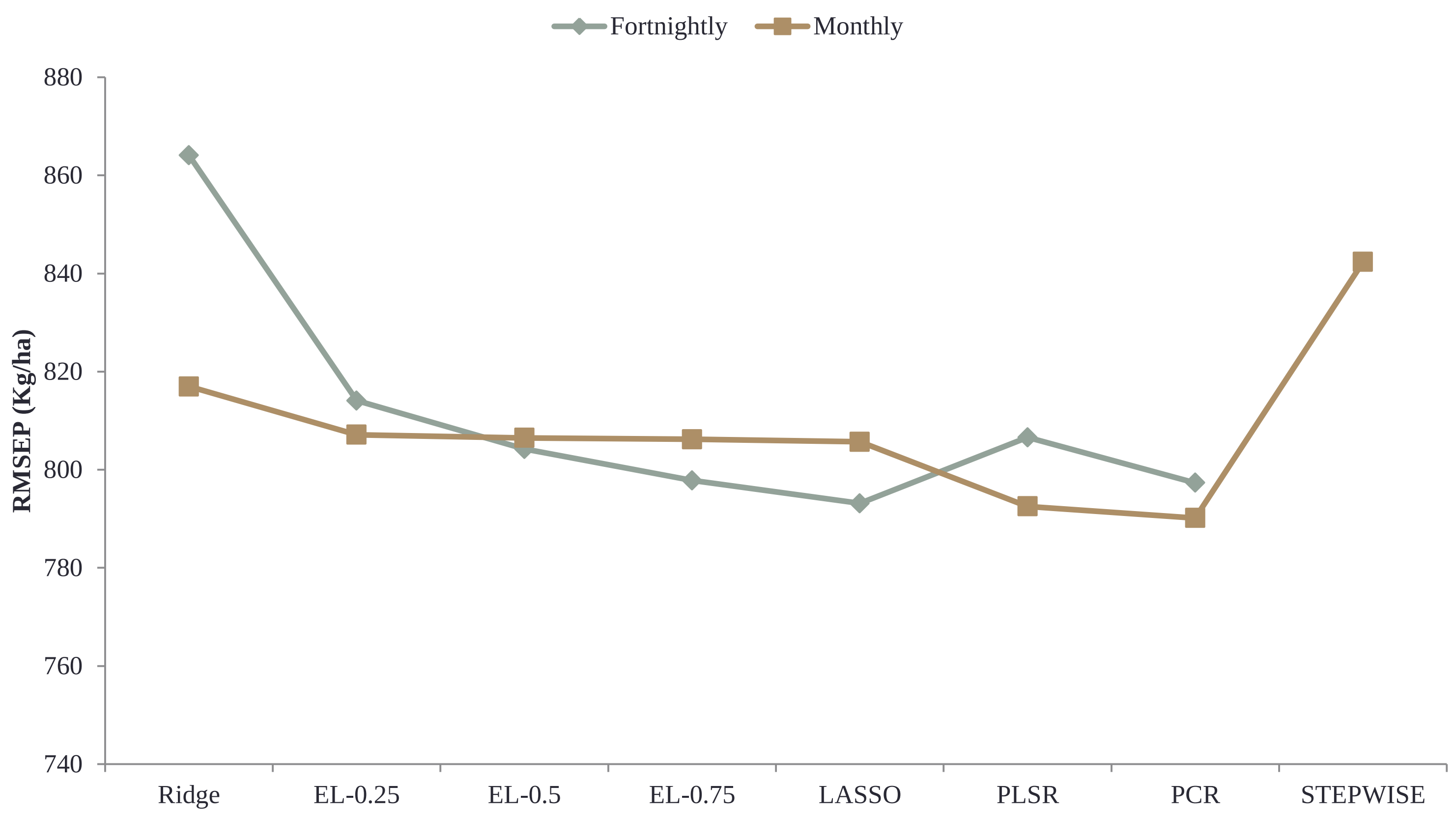
Intercomparison

- Prediction
  - Hold-one-year-out for cross validation
- Inference
  - Features remaining in the final models

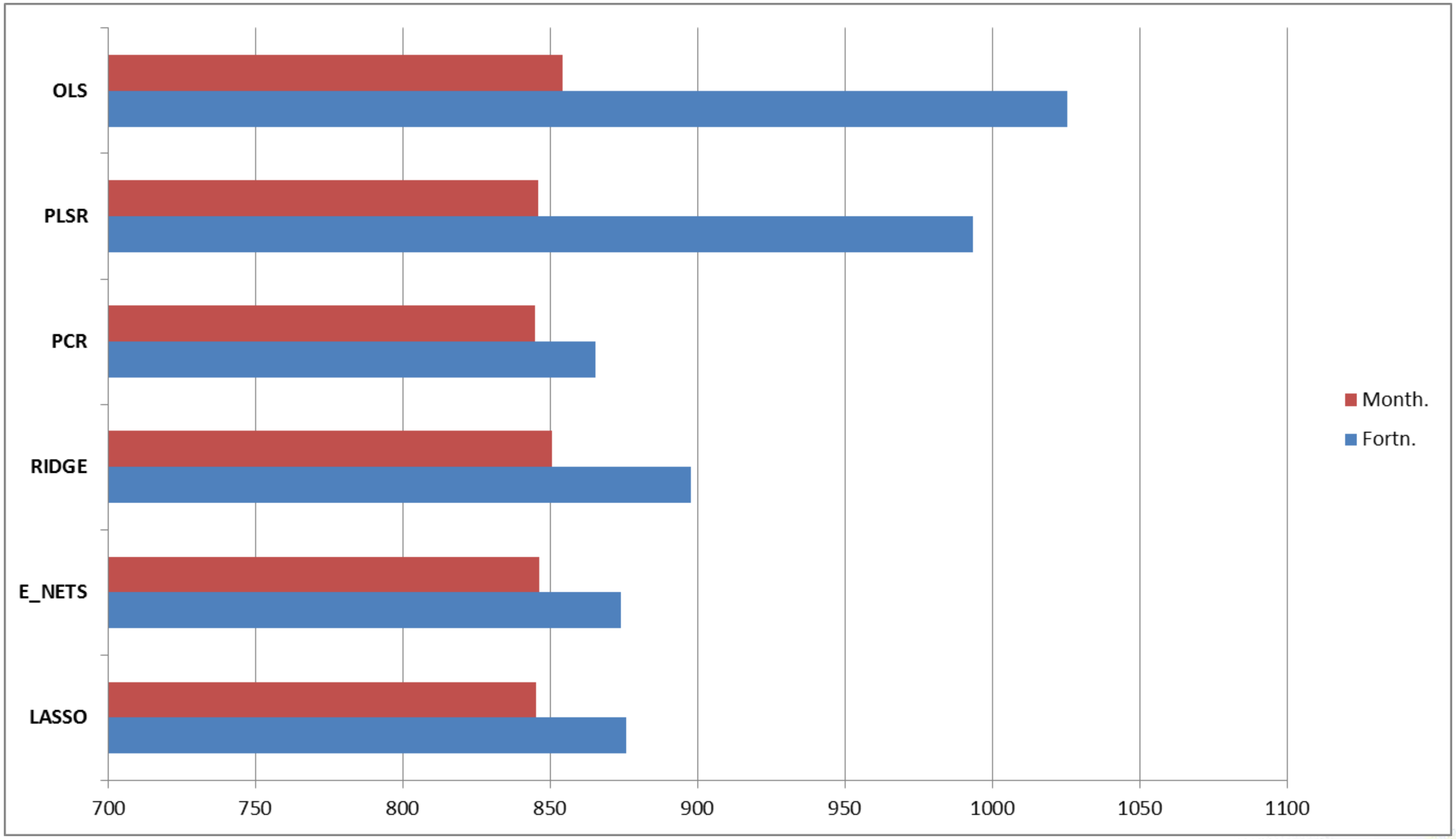
RESULTS

Prediction power

Root Mean Squared Error of Prediction - Denmark



Root Mean Squared Error of Prediction – All countries



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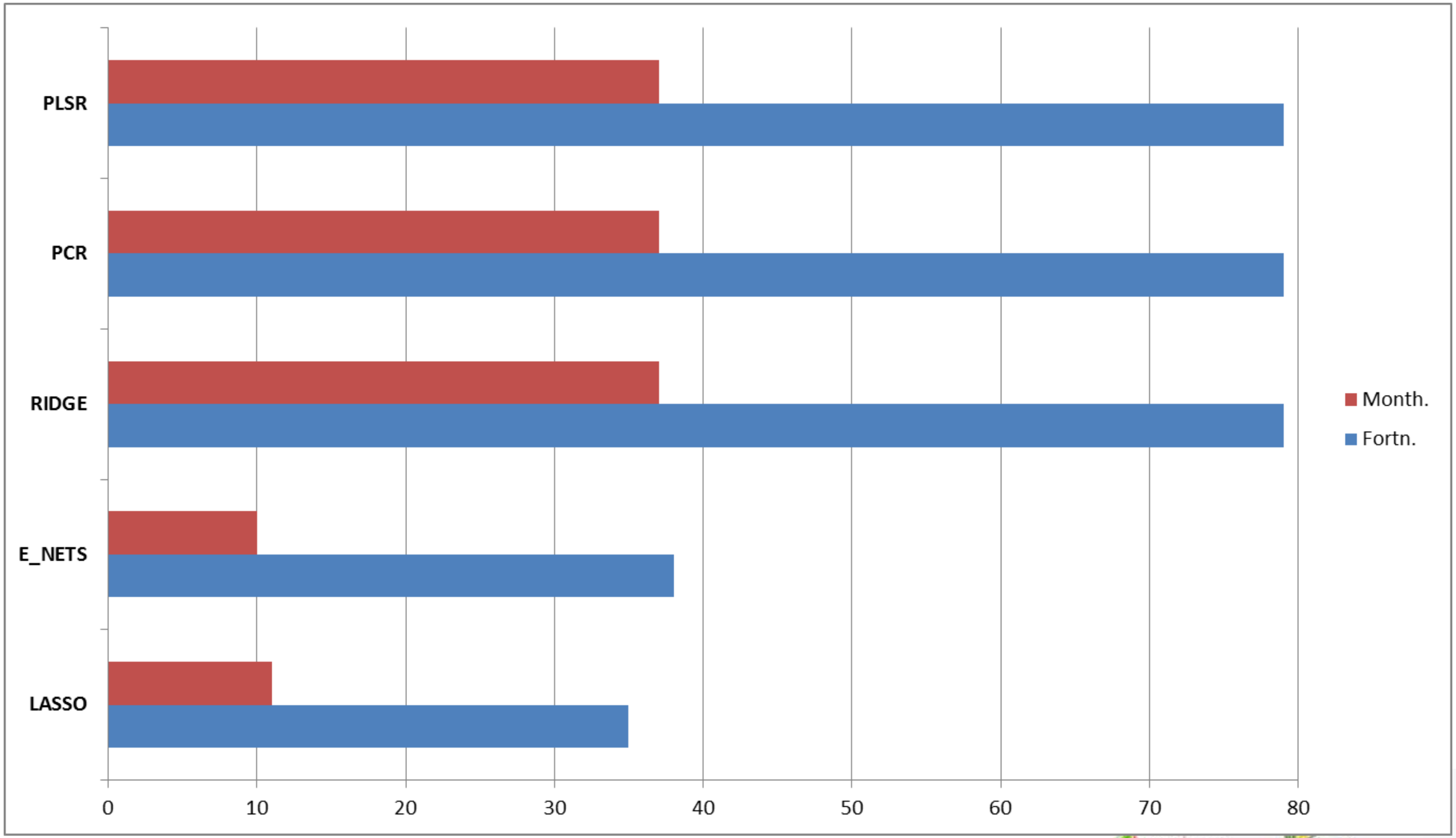
RESULTS

Inference power

Estimated Coefficients - Denmark

Start Date	01-08	15-08	29-08	12-09	26-09	10-10	24-10	07-11	21-11	05-12	19-12	02-01	16-01	30-01	13-02	27-02	12-03	26-03	09-04	23-04	07-05	21-05	04-06	18-06	02-07	16-07
End Date	14-08	28-08	11-09	25-09	09-10	23-10	06-11	20-11	04-12	18-12	01-01	15-01	29-01	12-02	26-02	11-03	25-03	08-04	22-04	06-05	20-05	03-06	17-06	01-07	15-07	29-07
Temperature																										
RIDGE	2	6	18	-1	-4	3	-12	25	1	-5	9	2	-10	-7	-3	-8	-3	1	32	24	25	4	-18	-2	2	-2
ELNET - Alpha =0.25							-23	19					0						44	29	20					
ELNET - Alpha =0.50							-29	9											31	39	13					
ELNET - Alpha =0.75							-32	3											22	48	10					
LASSO							-33												17	53	8					
PLSR	10	10	10	4	-1	-7	-16	12	0	-4	16	8	-13	-9	-3	-13	1	-2	13	11	12	0	-8	0	-7	-4
PCR	9	10	7	5	1	-11	-15	11	-7	-9	9	9	-20	-6	-6	-18	1	-1	12	4	7	2	0	1	-5	-2
OLS	9	-18	232	-212	-111	135	13	-68	-36	85	-3	-51	94	24	51	-49	203	-171	12	-150	425	67	-73	208	-87	-263
STEPWISE			144	-203	-126	101							70				108	-100			354			136		-285
Radiation																										
RIDGE	4	-17	-7	8	32	24	-27	-70	60	2	-29	-93	13	11	9	14	10	9	16	6	-3	5	-2	-6	-2	-2
ELNET - Alpha =0.25	3				37			-57											17							
ELNET - Alpha =0.50	6				34			-13											12							
ELNET - Alpha =0.75	9				32														10							
LASSO	11				31														8							
PLSR	16	-5	0	10	10	6	1	-3	0	1	-2	-1	2	-2	0	6	8	2	18	8	4	3	-7	-8	-12	-5
PCR	16	-3	2	13	8	8	3	-2	0	2	-2	0	4	-1	-4	11	10	-4	16	11	0	7	-3	-6	-12	-1
OLS	60	98	83	-67	84	-32	-195	-373	73	-216	399	-507	-48	381	-12	-16	-14	-44	132	-15	-129	-108	13	-19	25	113
STEPWISE		62			162			-397		-496				432					95		-99	-91				82
Precipitation																										
RIDGE	13	-2	-21	-19	-7	3	-9	-29	8	-9	-19	-1	-6	6	-32	-15	-6	-1	-1	-20	-11	-5	12	1	1	21
ELNET - Alpha =0.25			-7	-30				-47							-23					-2						
ELNET - Alpha =0.50				-34				-35							-21											
ELNET - Alpha =0.75				-36				-28							-19											
LASSO				-37				-23							-17											
PLSR	2	-2	-7	-12	-3	1	-12	-9	0	-2	-2	2	-3	0	-11	-6	-1	1	-3	-4	-4	-4	2	1	0	5
PCR	-3	2	-3	-6	-5	2	-7	-5	-2	-2	0	4	-4	0	-9	-6	-2	3	-4	-5	-1	5	3	2	3	4
OLS	51	-56	-46	-28	2	10	-47	-81	25	59	43	-86	83	57	-190	-75	156	124	8	-277	-32	-2	32	-79	52	138
STEPWISE		-41	-74					-142				-104		143	-122		173	119		-200				-78		126

Number of Significant Features in the final model - Czech



RESULTS

Uncertainties

Variance Decomposition – Yield projetction under climate change

$$V(Y) = V_M\left[E_{\varepsilon,\theta}(Y|M)\right]$$
$$+E_M[V_\theta(E_\varepsilon(Y|M,\theta)]$$
$$+E_M[E_\theta(V_\varepsilon(Y|M,\theta)]$$

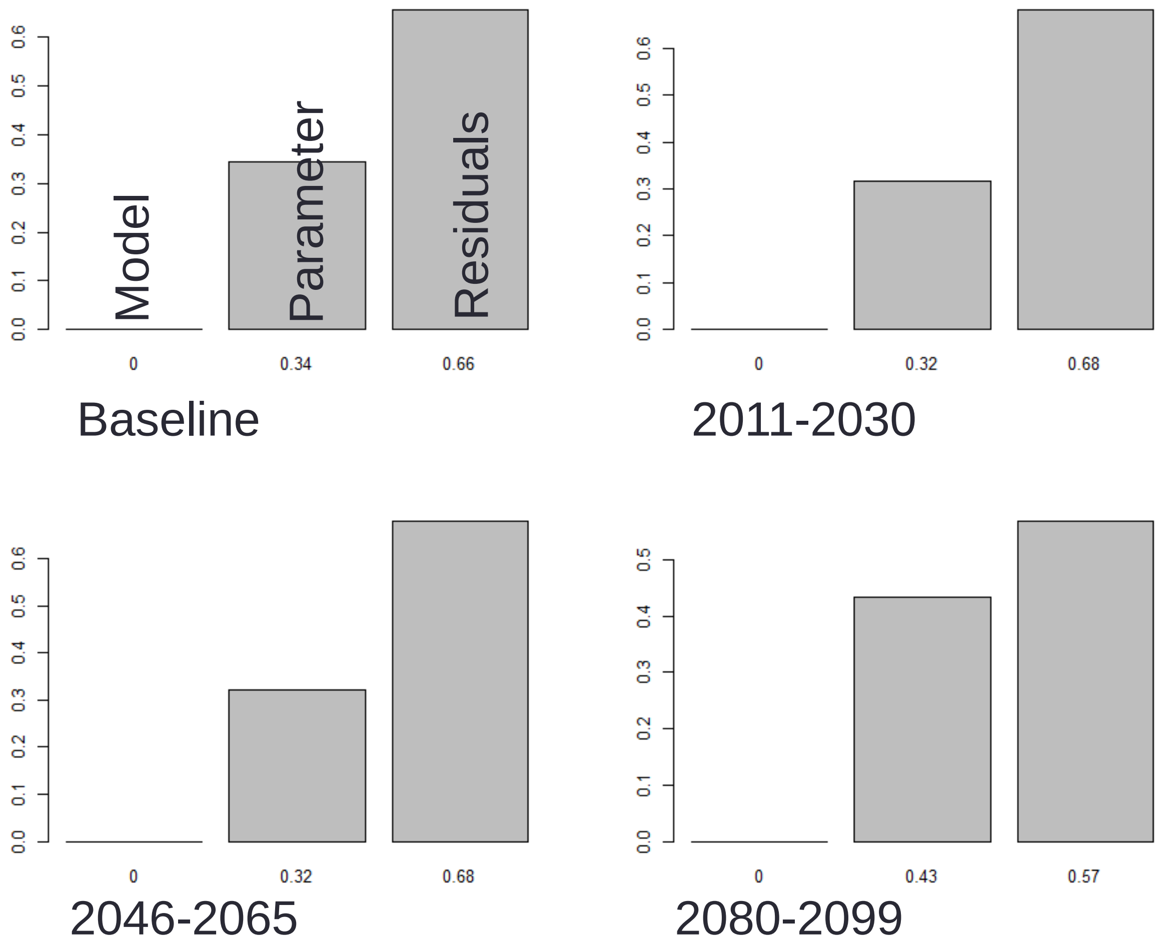
Where

M: Model

θ : Set of parameters

ε : Residual errors

Variance decomposition - Czech

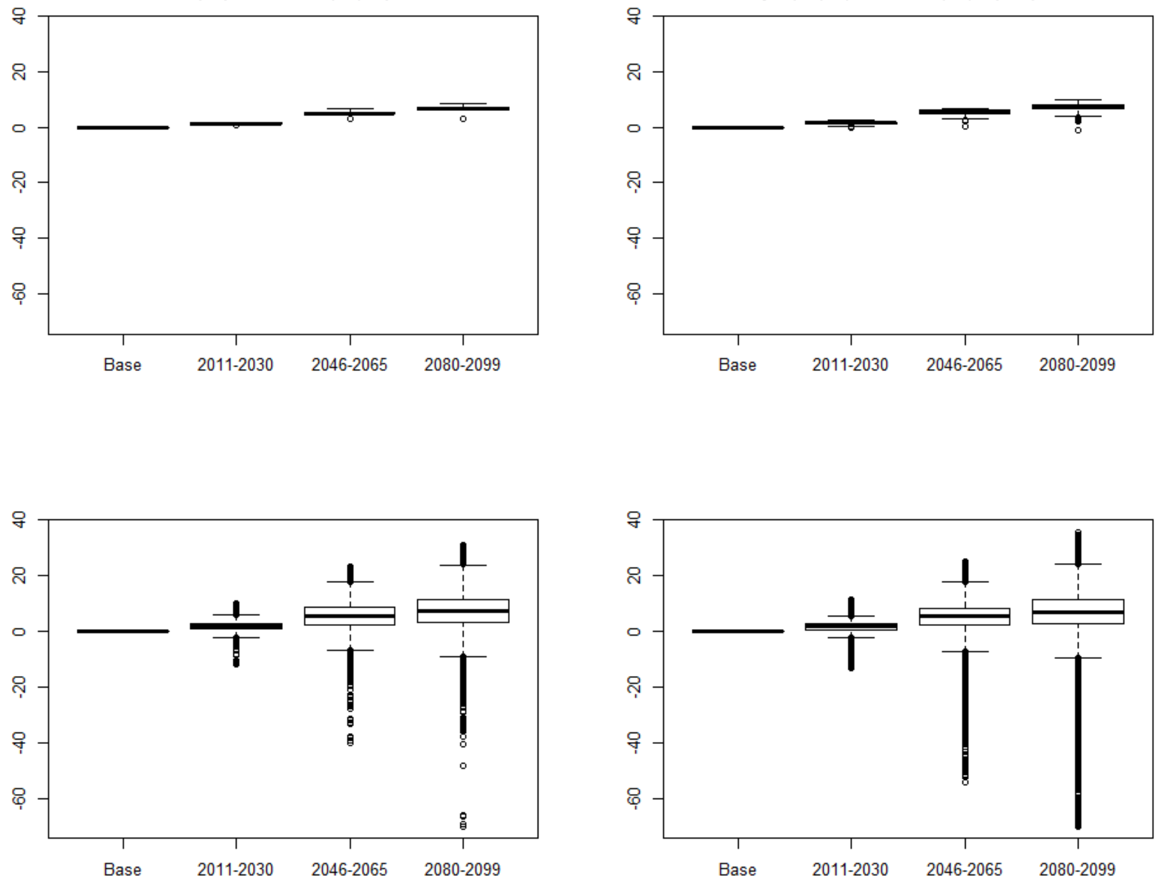


Effect of model and parameter uncertainty percent of yield change predictions - Czech

”Best” model ”Good” models

Main Sample

bootstrapping



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Conclusions

- State-of-the-art regression techniques could be useful, both in prediction and inference.
- Regression techniques can be useful in pointing out which climatic factors are influential for yield during which growth phases
- Cross-validation of regression models across space (beween countries) can provide a method for validating validity for use in climate change projections
- Regression techniques offer a direct method for addressing parameter uncertainty

THANK YOU!